Human Pulse and Respiratory Signal Analysis using a Robot Hand equipped with a Biomimetic Fingertip

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***Abstract*—Two key indicators of human health are pulse and respiratory rate. Being able to measure pulse (rate and rhythm) and respiratory rate (RR) in an emergency or search and rescue situation could be the difference between life and death. This paper presents novel algorithms that will equip a robot with the necessary skills to assess a human's pulse and RR. Algorithms that calculate heart beats per minute (bpm), Pulse to Pulse Interval (PPI), RR and Breath to Breath Interval (BBI) are presented. The bpm is used to classify if a heart rate is normal, bradycardic, or tachycardic. PPI is used to determine if the pulse rate is regular or in a form of arrhythmia. The RR and BBI are used to determine if the humans breathing is normal and regular. The results in this paper show that pulse and breathing were successfully measured and a subject's bpm and RR calculated using a trough detection method following a two stage noise reduction filter. Furthermore the robotic system proved to be capable of classifying the pulse as being regular or arrhythmic and the RR as being regular or irregular.**

I. Introduction

When assessing a person's condition in an emergency or rescue situation, responsiveness, respiratory rate (RR) and blood circulation are all critical measures of the subject's health. Reading a person's pulse is one common method of assessing their blood circulation. The pulse can be measured from numerous points around the human body, for example; from the posterior tibial at the ankle, the carotid artery at the neck or the radial artery at the wrist. However to read and analyse the pulse can require high levels of skill and experience from medical personnel. Measuring RR requires counting how many times the chest rises in one minute. This is a very tricky procedure as it is often completed visually and if the person is breathing weakly or visibility is poor, it may be difficult to distinguish movement in the chest particularly through clothing.

The heart pulse rate is the speed of the heart measured by how many beats it completes in one minute (bpm) and is normally measured on the wrist or neck. It is considered that a normal pulse (heart rate) for a resting adult ranges from 60-100bpm. However, heart rate can vary depending on age, physical size and needs, amongst other factors. Therefore any algorithms developed to measure bpm needs to be accurate in terms of the measurement and also intelligent such that it can understand varying heart rates. There are various commercially available machines and equipment available to monitor pulse rate, wrist bands and fingertip pulse oximeters for example. However, these methods require the subjects to be wearing a sensor or numerous in order to retrieve an accurate measurement of their pulse. Therefore, it can be difficult to measure one's pulse in an emergency situation when they are not wearing the aforementioned sensors.

RR is normally measured by watching the persons chest and counting how many times it raises in a given time, typically 60secs. However it can prove very difficult to see every breath. It is common to use a stethoscope or make contact with the chest wall when measuring one's RR [1]. However, in an emergency or rescue scenario it may not be possible for a medical professional to safely get close enough to place their hand on the individuals chest. It is estimated that a healthy adult should breath 12-20 times per minute when at rest [2]. Having a robot equipped with the necessary intelligence and skills to read RR using tactile sensors will prove to be extremely beneficial.

The purpose of this work is to ascertain if a robot hand equipped with sophisticated tactile sensors (biomimetic fingertips) is capable of accurately detecting and measuring pulse and breathing in a similar manner to how a human would. Building on previous work [3], the retrieval and calculation of pulse and respiratory rate, the PPI (i.e. time between detected pulses) and the BBI (i.e. time between detected breaths) are investigated in a preliminary experiment. Similar to a human fingertip, the biomimetic fingertips on the robot hand are capable of measuring vibration, thermal conductivity, static temperature and force. As in [3], the data source used for the pulse reading is vibration (as is used by a human when reading another's pulse) rather than light or electrical data. Building on the algorithm used in [3], experiments for measuring respiratory rate together with pulse rate are conducted. The data sources used for measuring breaths are vibration and thermal conductivity, used concurrently to ensure algorithm robustness. This work also work extends [3] by adding a second stage of filtering utilising wavelet algorithms, thus improving the overall noise reduction in the collected pulse and respiratory rate waveforms. The remainder of this paper is organised as follows: Section II presents a brief overview of related research in vital signs measuring instruments and methods. Section III describes the data collection and the algorithms developed in this work for pulse and breathing analysis. Section IV presents results for pulse rate, respiratory rate, PPI and BBI calculations. Conclusions and plans for future work are in presented Section V.

II. Background and Related Research

Noise reduction is vital for pulse detection and analysis process as pulse signals can be weak, non-stationary, low frequency signals which can be easily contaminated by background noise, such as respiratory or muscle movement [4]. Wang [5] presents a two stage noise reduction scheme for human pulse signal. Initially a wavelet packet transform (WPT) is employed to decompose the pulse signal and obtain the wavelet coefficients. Median filtering (MF) is then adopted for these coefficients to remove noise and the pulse signal is reconstructed based on low frequency coefficients. Following tests on several pulse signals collected in a clinic the algorithm was shown to filter noise effectively. Baseline wander of the pulse waveform can be caused by respiration or artefact motion during pulse data. Xu et al., [6] use a wavelet-based cascaded adaptive filter (CAF) to remove baseline wander. To evaluate the level of baseline wander, a new criterion was introduced: energy ratio (ER) of pulse waveform to baseline wander [6]. The baseline wander in pulse data can be significant or insignificant. When there is very little baseline wander, a wavelet filter may introduce some distortion [6]. The ER was used to determine the strategy required to remove the baseline wander. If the ER was greater than a given threshold, the baseline wander could only be removed by cubic spline estimation. Otherwise it had to be filtered by, in sequence, a discrete Meyer wavelet filter and the cubic spline estimation. The system was found to be efficient and robust in filtering various baseline wanders of pulse waveforms.

In contrast to focusing on noise reduction of the pulse waveform, other methods have focused on fast pulse wave detection and pulse wave analysis [7], [8], [9], [10]. Directed at establishing the presence of cardiac activity in an emergency Nenova and Iliev presented an automated algorithm for fast pulse wave detection [7], [8]. The algorithm was tested on a set of arterial pressure pulse waves from the internationally recognised MGH/MF waveform database from PhysioNet [11]. The algorithm demonstrated that it was capable of identifying cardiac pulsations even with manufactured artefacts (noise), however it was not tested on a human in a real life scenario. Furthermore, the machine required to take the pulse from the neck is a customised machine which must be correctly fitted to the individual in order to identify the cardiac pulsation. Suzuki et al. developed an arrhythmic pulse detection algorithm from PPG data measured in daily life using a wearable PPG sensor. Although the PPG sensors are a simpler device compared with an ECG device, PPG is very sensitive to artefacts, e.g. body movement [9]. Suzuki et al. focus their sensor on identifying signs of arrhythmia and although it was confirmed that the algorithm could detect irregular pulse without misdetection of body movement, the method requires the constant use of a wearable sensor which will not always be practical for a user in everyday life or in a rescue scenario.

Measuring Respiratory Rate (RR) in humans has proven to be a difficult task and prone to error [1]. Morley et al. [1] measure respiratory rate in babies under six months old and report that it is much more accurate to use a stethoscope or to physically place a hand on the child's chest to count the movements that represent breathing. Most recently, numerous techniques aimed at contactless respiration monitoring have been investigated. Many of these attempts are based on acoustics, radar detection or time-of-flight cameras for example [12] to estimate the frequency of the chest movements during respiration. Some attempts at visual detection make use of an infra-red camera to detect motion in the scene [13]. Other methods focus on processing images obtained from regular cameras [14]. Furthermore vision or acoustic only based systems may prove unreliable in noisy emergency environments.

In summary the literature presents methods that are capable of recognising and analysing pulse wave signals and respiratory rate, but there is still a need for a system which can analyse vital signs in an emergency and mobile scenario. The aim of this work is to utilise a more general mobile robot's tactile sensor to be able to identify two human vital signs in the event of an emergency. This will in turn provide a "first response" service to a user or could be used to determine a human's health status in an emergency rescue scenario before risking further human life.

III. Methodology

A. Robot used for Pulse and Respiratory Measurement

The Shadow robot hand [15], equipped with three BioTAC™ sensors from Syntouch® was used to collect pulse and respiratory data from a human. The Shadow robot hand has similar dexterity to a human hand allowing it to mimic, to some extent, the actions required to collect pulse and respiratory data from a human. The BioTAC is a tactile sensor which is shaped like a human fingertip and is liquid filled, giving it similar compliance to a human fingertip [16], [17]. Like a human finger, it is capable of detecting a full range of cutaneous sensory information: forces, micro vibrations and temperature. Figure 1 shows a cross section view of the BioTAC fingertip.

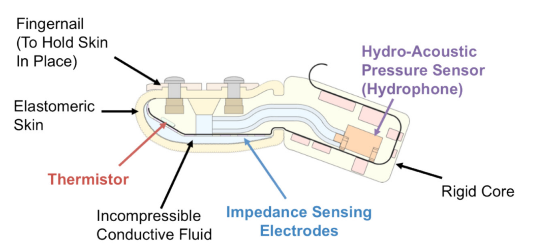


Figure 1. Cross Section View of BioTAC Fingertip Tactile Sensor [18]

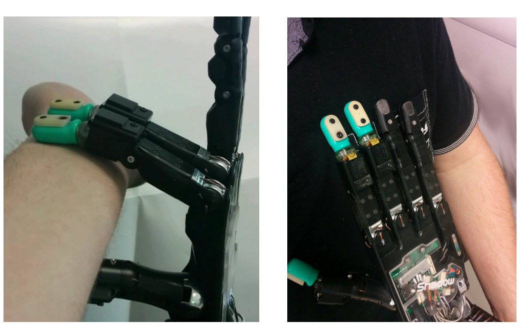
As outlined in [17], [3], the BioTAC fingertip measures force applied across an array of 19 electrodes. It measures absolute temperature (TDC) and thermal flow (TAC); the rate at which heat is leaving the fingertip and transferring to what is in contact with. Finally it measures vibration and outputs two different values, one is a DC pressure signal (PDC) which is the reading obtained after passing through a low pass filter and the other is an AC pressure signal (PAC) which has been passed through a band pass filter.

B. Data Collection

For collecting both pulse and respiratory data, the BioTAC fingertip is allowed 15-20 mins to reach its steady state temperature (approximately 31°C, 10°C above ambient) after being first powered on, similar to the experiments carried out in [17] and [19]. Through Ethercat on the Shadow Hand, the PAC, PDC, TAC and TDC values from the BioTAC fingertip are recorded at 100Hz. These values are recorded using ROS and a dataset for PAC, PDC and TAC data was formed using Python.

1) Pulse Measurement: The PAC values can be used to determine the vibration (of the internal conductive fluid) caused by the pulse when the fingertip is pressed against the radial artery. To press the finger against the radial artery the Shadow hand positions the thumb below the wrist and moves the first finger (FF) and middle finger (MF) in small increments towards the radial artery on the ventral aspect of the wrist on the side of the thumb of a human subject. Using the electrodes in the BioTAC fingertip the force applied to the finger is constantly measured and once sufficient contact is made with the wrist by the FF and MF, the fingers stop moving and the system begins recording the PAC data. The subject was a healthy male aged 32 years old. As seen in Figure 2(a), this action replicates the action of a human when attempting to measure a subject's pulse by using the fingers to contact the wrist and count how many beats are felt in 30 secs. Three datasets of 30 secs each were collected when the individual was at rest and one dataset was collected immediately after the individual completed 5 minutes of exercise.

2) Respiratory Measurement: In order to determine the RR of the same human subject, contact with the chest was made using the Shadow Hand. The hand started in an open position and both the FF and MF moved towards the upper left side of the subject's chest in small increments, as shown in Figure 2(b). The electrodes on the BioTAC were constantly monitored until sufficient contact was made with the chest. In this case static vibration data (PDC) was used to identify the movements of the chest wall more effectively than PAC. Furthermore, as breathing can cause a lot of added artefacts and noise, it hypothesised that it would be more robust to measure a second modality together with vibration data. As the skin of the subject pushes against the inside clothing during breathing the fingertip senses the change in temperature causing the thermal conductivity value to fluctuate as a result of the concentrated indirect contact with the skin via the clothing. Therefore TAC data and PDC data were recorded to assess respiratory rate to add robustness to the algorithm. Two datasets of 60 secs each were collected when the individual was at rest and breathing normally and two datasets were collected when the individual was breathing heavily.



(a) (b)

Figure 2. (a) Image showing the Shadow Hand taking the subjects pulse (b) Image showing the Shadow Hand resting on the subjects chest to measure RR

C. Waveform Pre-processing

In order to reduce noise and smooth the waveform of both the pulse and respiratory data, two stages of filtering was applied to the data. As human heart beat is a low frequency sound, various low pass filters were evaluated for the first stage of filtering. The filtered signal was visually inspected to determine if all of the troughs representing heart beats and breaths taken in the waveform were preserved and as many incorrect troughs (i.e. noise), as possible, were removed. To thoroughly evaluate each filter, various cut off frequencies and filter orders were applied. Empirically, it was found that a Butterworth infinite impulse response (IIR) filter with a cut off frequency of 10Hz and a filter order of 10 performed best by demonstrating a preferred smoothing without loss of data. Therefore, this filter was used throughout the pulse and respiratory experiments presented. The second stage of filtering was completed by using a Discrete wavelet transform (DWT) wavelet algorithm. SPL wavelet filtering algorithm with a scaling function of 5 was empirically found to be the most effective configuration and therefore was applied to all waveforms collected.

D. Trough Detection, BPM and RR calculation

From visual inspection of the filtered pulse and respiratory data waveforms, it is clear that there is a prominent trough representing each pulse (heart beat) and breath taken. Therefore, by identifying and calculating the number of troughs in a 30 second window of the pulse waveform a calculation of the subject's bpm can be completed by multiplying the number of troughs by two. As breathing is less frequent than heart beats it is recommended that RR is calculated over a 60 second interval, therefore by identifying the number of troughs within a 60 second period of the respiratory data the subjects RR can be calculated. This calculation is completed for both the TAC and PDC waveforms collected for the RR in order to compare and ensure both data sets produce the same calculated RR.

The troughs for pulse and respiratory rate are visually evident in the graphs showing the DWT filtered waveform of the PAC data used for pulse detection in Figure 3(b) and the TAC data used for breath detection in Figure 3(d). Although the troughs are clearly visual when inspecting the graphs, it is required that they are detected automatically in order to calculate the bpm and RR of a subject. In order to detect prominent troughs in the waveform a modified version of a publicly available function called "peakdet" in MATLAB is utilised. This function detects the local maxima and minima in a wave signal. The function uses a threshold (default 0.5) of the difference between the suspected trough and its surrounding values in order to declare it as a trough.

However, due to the range of variance within the datasets for each modality, a dynamic threshold was developed for use with this function as the troughs in the graphs are quite prominent. This also helps to avoid any outstanding residual noise from being incorrectly detected as a trough. As the trough is required to be detected with respect to the resting waveform the dynamic threshold is calculated for each modality using the standard deviation and is given by.

$$dt_m = x \times \sigma \tag{1}$$

where dt_m is the dynamic threshold for each modality, x is the factor determined by which modality is being analysed and σ is the standard deviation. Various multiples of σ were empirically applied and tested for each modality until an optimal value for the threshold was determined enabling accurate detection of troughs in each case. For $m = PAC$, $x = \frac{7}{4}$, for $m = TAC$, $x = \frac{2}{5}$ and for $m = PDC$, $x = 1$. The algorithm automatically assigns the correct threshold depending on which modality the dataset has been collected from.

E. Pulse to Pulse (PPI) and Breath to Breath Interval (BBI) Calculation

In order to determine if a pulse is regular, the time difference between each detected pulse, the pulse to pulse interval (PPI), is calculated across the waveform. An individual may have a normal heart rate (i.e. between 60-100bpm) but their pulse may not be beating at regular time intervals or may be following an irregular pattern. Therefore, they should be classed as having an arrhythmic heart beat or a sinus arrhythmia. Likewise, in order to determine if the subject's breathing is regular the breath to breath interval (BBI) is calculated across the waveform. As the next series of equations have been adapted from previous work [3] so that they can be used to calculate both the PPI and BBI from their respective datasets, the PPI and BBI shall be referred to as the interval I in the remaining equations.

The expected PPI (time difference between each detected pulse) and BBI (time difference between each detected breath) in the given time of the data collected (i.e. 30 secs and 60 secs respectively) are calculated in order for the heart rate and RR to be classified as regular and healthy. This expected interval, I is defined as:

$$I_{reg} = \frac{t_{wf}}{N_{td}} \tag{2}$$

where I_{reg} is the expected I (s) for the heart rate or RR to be regular, t_{wf} is the complete length of time (s) of the waveform and N_{td} is the number of troughs detected in the waveform.

The I between each individual pulse or breath detected in the waveform is calculated by:

$$I_{indiv} = t_{ct} - t_{pt} \tag{3}$$

where I_{indiv} is the I between each individual trough detected (s), t_{ct} is the time stamp of the current trough detection (s) and t_{pt} is the time stamp of the previous trough detected. In order to reduce outliers or any residual noise in the waveform affecting the I classification, along with the I being calculated at every point, a sliding window was used and an average for I within the window at each step is calculated. The sliding window is designed to move in time steps of 0.5 seconds and have a length of 5 seconds. Equation 4 determines how many sample windows will be analysed across the entire datasets.

$$N_{sw} = \frac{N_{tds} - (l_{sw} \times N_{dps})}{(TS_{sw} \times N_{dps})} \tag{4}$$

where N_{sw} is the number of sample windows analysed across the complete dataset, N_{tds} is the number of data points in the complete dataset, l_{sw} is the length of the sliding window (s), N_{dps} is the number of data points recorded per second, and TS_{sw} is the time step of the sliding window (s). For the collected pulse data, this resulted in 50 samples of data across the entire wavelength and 108 samples for the collected respiratory data. The average I for each window of data was calculated as:

$$I_{win} = \frac{\sum_{I_{tdw}=1}^{N_{tdw}} I_{tdw}}{N_{tdw}} \tag{5}$$

where I_{win} is the average I (s) between the troughs detected within the window, I_{tdw} is the individual I between the troughs detected within the window (s) and N_{tdw} is the number of troughs detected within the window.

I_{indiv} and I_{win} are then analysed against the expected I required for a regular and healthy pulse rate (equation 2) in order to determine if the pulse is regular or arrhythmic. Due to the nature of the data, it is not realistic to expect every individual I reading or the average I reading of a 5 second window of data to be exactly the same as the rhythmic average. Therefore, in this preliminary study we have empirically selected a tolerance of $\pm 15\%$ of the rhythmic average PPI at each pulse detected to classify between regular (healthy) and arrhythmic pulse rates. If the individuals PPI is within this tolerance then the heart rate is classified as being regular. Likewise the I_{indiv} and I_{win} are analysed to determine if the subjects breathing is regular or irregular. A similar tolerance is suggested for the BBI to be within for the breathing to remain classified as regular.

IV. Results

A. BPM calculation and Analysis

Application of the two stage filtering process, a low band-pass Butterworth IIR filter followed by DWT noise reduction, to the raw data successfully removed noise and smoothed the waveform to a level that would allow for successful trough and therefore pulse and breath detection; the data contained significantly less noise than that presented in previous work [3] using a one stage filter process. Figure 3(a) and 3(b) show the PAC waveforms of dataset 1 recorded from the individual's wrist whilst at rest before and after the application of the two stage filter respectively. Figure 3(b) also shows the troughs (pulse in this case) detected by the trough detection algorithm which are highlighted by blue stars. Figure 3(c) and 3(d) show the TAC waveforms of dataset 1 recorded from the individuals chest before and after filtering respectively. Figure 3(d) also shows the troughs detected (breaths in this case) by the trough detection algorithm which are highlighted by blue stars. The trough detection algorithm has proven to work well in the majority of cases. The pulse detection algorithm worked especially well in the waveforms collected when the individual was at rest enabling accurate bpm calculations.

Calculation of the average heart rate (bpm) for each dataset (three for the individual at rest and one immediately after exercise) and the heart rate classification of either normal heart rate, bradycardic or tachycardic can be seen in Table I. The actual bpm (measured manually from the individual's wrist), at the time of rest before exercising was 62bpm. It can be seen that set 1 and set 3 results in accurate calculation of the bpm and set 2 has calculated a value quite close to 62bpm and therefore has still correctly determined the heart rate as being a normal heart rate. This table is similar to that presented

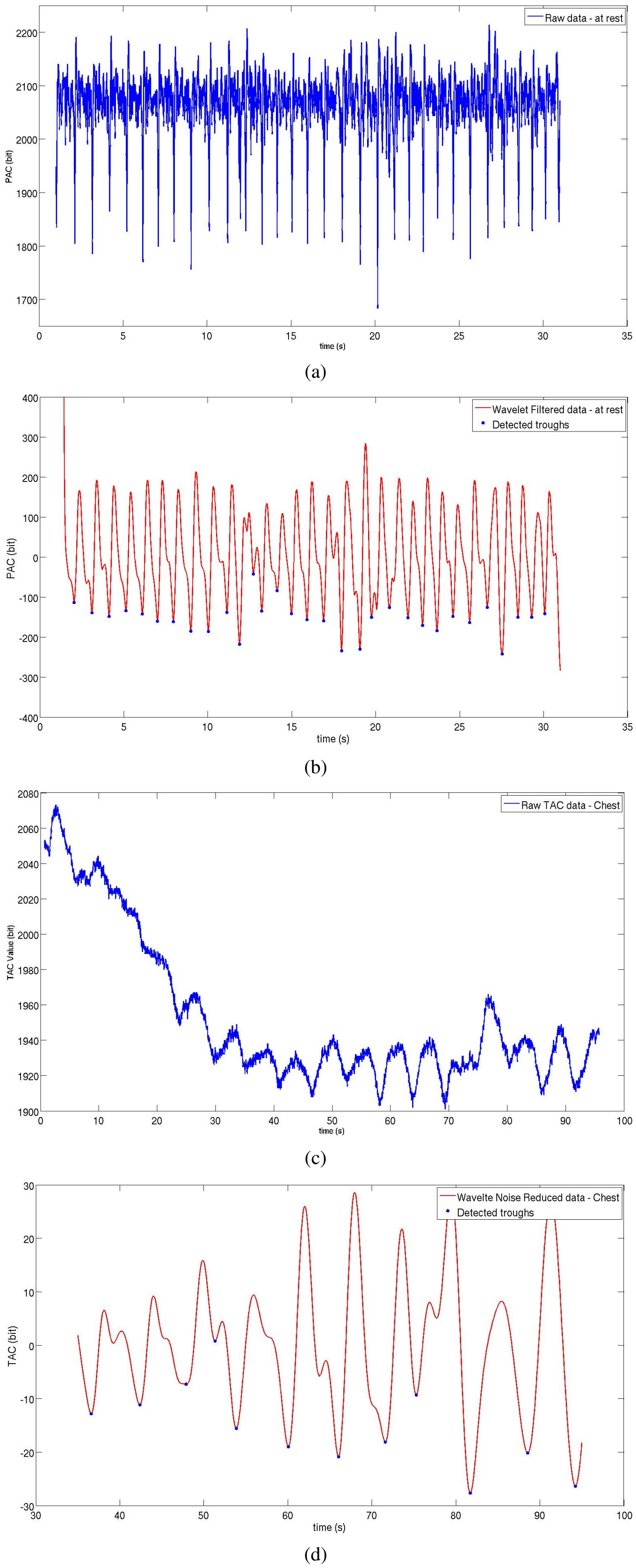


Figure 3. Graphs showing the raw PAC vibration data collected from the individual's wrist whilst at rest and from the raw TAC thermal conductivity data collected individuals chest respectively (a+c); Graphs showing the PAC vibration data after the two filter was applied and showing the detected troughs from the pulse data on the wrist and the respiratory data on the chest whilst at rest respectively (b+d).

in [3], however this work demonstrates an improvement in accuracy for set 3 from 60bpm in [3] to 62bpm which is without error. This is mainly due to the increase in performance of the preprocessing by implementing the two stage filter.

Table I. TABLE COMPARING THE BPM EXPERIMENTAL RESULTS.

Individuals State	**BPM**	**Heart Rate Classification**
At rest - set 1	62	Normal
At rest - set 2	64	Normal
At rest - set 3	62	Normal
After 5mins of exercise	96	Normal

Calculation of the respiratory rate (RR) for each dataset (two for the individual at rest, breathing normally and two for the individual at rest, breathing heavily) and the respiratory rate classification of either slow, normal or fast breathing rate can be seen in Table II.

The actual manually counted RR from the individual's breathing at the time of rest is 12 breaths per minute when breathing normally and 13 breaths per min when breathing heavily. It can be seen from the results in Table II that the algorithm was one breath short in one occasion when using the TAC data and one breath short on both occasions when using the PDC data. Unfortunately, this meant that for set 1 the user was classified as having a slow RR when this was not the case. Furthermore, it can be seen that when the subject was breathing heavily the system detected more breaths (perfectly correct in two cases). Future work will address the sensitivity of the breath detection and attempt to improve it for lighter breathing.

Table II. TABLE COMPARING THE RR EXPERIMENTAL RESULTS.

Individuals State	**RR - TAC Reading**	**RR - PDC Reading**	**Respiratory Classification**
At rest (breathing normally)- set 1	11	11	Slow
At rest (breathing normally)- set 2	12	11	Normal
At rest (breathing heavily)- set 1	13	15	Normal
At rest (breathing heavily)- set 2	12	13	Normal

To validate the algorithm used for bpm calculation, we used a benchmark dataset available from PhysioNet [11]. The peaks defining pulse across all the waveforms were correctly identified and used to calculate the correct bpm in the majority of test sets. Validation of the algorithm using the ECG signals in this dataset also demonstrates robustness and adaptability of the proposed approach.

B. PPI and BBI Calculation and analysis

The pulse to pulse (PPIs) and breath to breath (BBIs) intervals were successfully calculated both between individual troughs detected and the average of troughs detected within a sliding window for each dataset. A graph showing an example of the calculated PPI between the individual pulses and the average within each sliding window for the dataset collected when the subject was at rest is shown in Figure 4. Also plotted on the graph are the upper and lower limits of the 15% tolerance of the overall average PPI required for regular pulse rate [3].

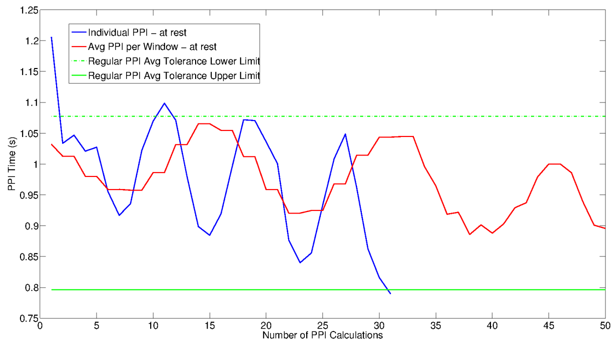


Figure 4. The calculated PPI between the individual pulses, the average PPI within each sliding window and the tolerance of the overall average PPI required for regular pulse rate for the dataset collected when the subject was at rest

Figure 4 shows that the average PPI calculated between each individual pulse detected can dip and peak outside of the average PPI tolerance and is a much sharper curve. This would indicate that the individual has an arrhythmic heart rate. At all times the PPI is within the average PPI tolerance and therefore this pulse would be classified as being a regular pulse pattern which indeed is the case. The BBI calculations also proved that the subjects breathing was regular, as indeed was the case.

V. Conclusion and Future Work

Algorithms to equip a first responder robot with the skills necessary to assess two of a human's vital signs in an emergency situation is presented. A method for detecting a human's pulse, by making contact with the radial artery, and respiratory rate, by making contact with the chest, using a BioTAC robotic fingertip is presented. The calculation of the subject's bpm and RR is also completed. The robotic system is able to determine whether a person has a regular heart rate or is bradycardic or tachycardic and whether the person has a slow, normal or fast RR. A robust noise reduction algorithm was presented by introducing a second stage of filtering in the form of a DWT wavelet algorithm to reduce noise before completing trough detection. Determining the time between pulses (PPI) and breaths (BBI) is also important as this will evidently show if the individuals pulse is regular or in a form of arrhythmia and if the persons breathing is regular or irregular. Arrhythmic beat rates can represent signs of disease. The methods presented performed well for pulses recorded from the subject and for breaths recorded when the subject was breathing heavy and was slightly less accurate when the subject was breathing normally.

The methods presented have been evaluated on data collected from one subject and future work will include further testing on a wider range of subjects with various heart rates, pulse rhythms and respiratory rates in order to test their accuracy thoroughly. Ethical approval has now been granted for data collection from a large. Additionally we will include investigating how to make the algorithm more sensitive to light breathing, less chest movement and the case of movement of the subject for both pulse and respiratory rate data collection. Furthermore, future work will include assessing another one of a human's vital sign using a robot platform, namely Capillary Refill Time (CRT).

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